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System Identification of A Small Unmanned Aerial Vehicle Based on Time and Frequency Domain Technologies

Yulin Nong[1], Zaikang Qi[2]
[1]*Department of Mechanical Engineering*
McGill University
3430 University, Montreal, QC, H3A 2A7, Canada
nongyulin@cim.mcgill.ca
[2]*Department of Aerospace Science and Engineering*
Beijing Institute of Technology
Beijing, 100081, China
qzk@bit.edu.cn

Defu Lin
Department of Aerospace Science and Engineering
Beijing Institute of Technology
Beijing, 100081, China
lindf@bit.edu.cn

***Abstract*— The usage of system identification has been increasing in small unmanned aerial vehicle (UAV) model development. Most of previous methods for small UAV model identification has limitations in deriving an accurate model with wide frequency spectrum, or the identification results rely on the selection of weight parameters. These motive us to seek an efficient method to obtain accurate small UAV models. The method proposed in this paper uses pseudo-random signal (PRS) as test signal in small UAV model identification experiment for the first time. By using PRS, a small UAV's modes can be stimulated sufficiently. In this method, we also combine the advantages of time and frequency domain identification technologies together by increasing the order of target models in time domain identification and then deceasing model order by using frequency domain identification. The model validation results in time and frequency domain proved the fidelity of identified models and feasibility of our proposed small UAV model identification method.**

***Index Terms*— small UAVs, pseudo-random signal, time domain identification, frequency domain identification**

I. Introduction

Small unmanned aerial vehicles (UAVs) have obtained increasing attention in both practical and academic fields in recent decades. Small UAVs can not only be used for environment exploration, mapping and aerial cinematography, but can also be used in specialized tasks in hazardous environments, where risks are high to pilots or human presence is not necessary. Lots of research groups construct their own UAV platforms for different research purposes [1][2][3]. Two kinds of small UAVs are widely used in recent time, one of which is a fixed-wing UAV and the other is a rotor helicopter UAV. A fixed-wing UAV gains the advantages such as fast maneuvering and easier to be controlled than a helicopter UAV. However, a helicopter UAV can perform hovering motion, which cannot be achieved by a fixed-wing UAV.

System mathematical models of fixed-wing UAVs and rotor helicopter UAVs are well known[4][5]. However, difficulties arise from extending the usage of these models from large aircrafts to small UAVs. Because these small UAVs display some special characteristics corresponding to their geometry size, such as small mass, limited payload capability and high maneuverability. Besides, control system and onboard avionics, and actuators of small UAV are always simpler than large aircrafts. So, sometimes, models of a large aircraft cannot be directly used for a small UAV .

There are mainly two ways of modeling a small UAV's models. The first one is theoretical analysis, such as Newton-Euler equations, Lagrange principle and aerodynamic principles. The second one is statistical analysis based on experiments and/or data collection. Deriving a system model by system identification method belongs to the later. Basic principles of system identification method can be find in [7][8]. The main problems in system identification include experiment design, model structure selection, parameter estimation and model validation.

As we know, a small UAV which can perfectly carry out required missions should have a well designed physical structure and/or a high performance autopilot. Unfortunately, both the physical structure and the autopilot design rely on the mastered knowledge of the UAV system characteristics. The more knowledge we have of a certain small UAV, the easier it will be for us to improve this small UAV's physical construction and design better control systems and perform better maneuvering. Researches carried out on small UAVs model identification will benefit understanding and promoting small UAVs comprehensive system characteristics. Cai *et al.* [3] injected a set of carefully selected sinusoidal signals with different frequencies to their small helicopter's yaw control channel when the helicopter was under trimmed flight condition. A yaw channel model was derived here. Jung *et al.* used theoretical analysis and batch identification method to derive and estimate aerodynamic force and moment coefficients of their fixed-wing UAV [9]. CIFER developed by Ames Research Center is a mature commercial aircraft system identification software package. It is based on frequency identification principles and is fully described in [8]. Mettler *et al.* used CIFER in their small size unmanned helicopter dynamics parameter identification [11]. Niño *et al.* used CIFER in their novel Micro Air Vehicle (MAV) model identification [2]. The identified longitudinal and lateral models have been validated in time domain. But in model simplification procedure, they just killed the high frequency zeros and poles in their high order models, which was actually worthy of further consideration. One disadvantage of using frequency model identification technology is that the fidelity of identified model relies on the selection of the frequency range of the test signals, such as the selected frequency boundary of sine sweeps. And researchers selected the test signal frequency rang mainly according to the dominant dynamics of a small UAV, which means some basic dynamic characteristics of the small UAV are required in the model identification process. In [12], Salman *et al.* used a nonlinear mapping identification in their fixed-wing UAV model identification work. However, the identification results directly rely on selection of weight matrix K in their identification procedure. System identification method is also used to derive some innovative constructed small UAVs. In [10], Derafa *et al.* used system identification method to estimate a four rotors Helicopter parameter.

In our project, we built a small UAV flight platform, called SWAN-UAV, which is shown in Fig.2. The ultimate goal for our UAV research work is to build a supper robust and highly maneuverable unmanned aerial vehicle for surveillance, watch and autonomous navigation.

In this paper, we propose our system identification method to identify SWAN-UAV's models for longitudinal and lateral channels. In order to stimulate different modes of a small UAV, a pseudo-random signal (PRS) is injected to the small UAV's control signal during trimmed flight, which is different from selecting test signals in certain frequency interval in frequency domain identification method. In our method, we identify small UAV's high order models firstly by time domain identification method, and than decrease the order of the identified models by frequency domain identification method, combining the advantages of time domain and frequency domain identification methods together, which is different from previous UAV system identification methods. And the SWAN-UAV model validation in frequency domain and time domain demonstrate the fidelity of our identified models.

The outline of this paper is as follows. In section II, we provide a elaborate description of our proposed method of system identification of small UAV. The feasibility and identifiability of closed-loop identification are discussed, and the identification principles in our method are given at here. In section III, the SWAN-UAV system and the designed flight experiment procedure are introduced, and experiment results are given. The identified models are provided in section IV. In order to verify the fidelity of the identified SWAN-UAV models, frequency domain and time domain model validations are presented in section V. Finally, in section VI, we draw some conclusions and comments.

II. PROPOSED METHOD OF SYSTEM IDENTIFICATION OF A SMALL UAV

In order to give a clear picture of the proposed method, the whole process of a small UAV system identification is provided at the beginning of this part. Then the theories used in our method are illustrated later.

A. A Small UAV System Identification Process

Traditionally, the system identification experiment is designed under the precondition of open-loop control , so the input signal $u(t)$ can be controlled by humans in any time. In [11], the author announced that to ensure the efficiency of the system identification of small UAVs, it was important to conduct the flight experiments in open-loop condition. However, all small UAVs are designed to finish assigned tasks independently. Based on a small UAV's flight mission characteristics and auto-control requirements, closed-loop identification is needed and it hopes that model identification can be carried out on-line. Only by achieving these goals can the model identification be used to assist control optimization without manual assistance, whenever the flight condition changes from one to another. The feasibility, identifiability and efficiency of the closed-loop identification method for small UAVs have been demonstrated in [13]. Using a small UAV's mathematical model in [14], the models in open control loop, closed control loop and attitude control loop are successfully identified and compared in [13]. The identified models in the closed control loops show great coherence with the identified model in the open control loop. In our paper, the system identification is carried out in a closed control loop condition.

The schematic diagram of the proposed small UAV system identification process is shown in Fig.1. There are two structure-function modules in this method. The first one is the small UAV closed-loop system. This module includes a small UAV's hardware and the autopilot control system and can work independently in flight tasks.

To stimulate a small UAV's different modes in a flight experiment, a test signal will be injected into the small UAV's original control signal $U(t)$. This test signal need to be well selected so as to not affect UAV's normal flight during experiments.

Then, signals required in the identification algorithm will be selected and stored. Usually, all input and output signals could be sampled and recorded by autopilot based on the autopilot's processing frequency and storage ability. One

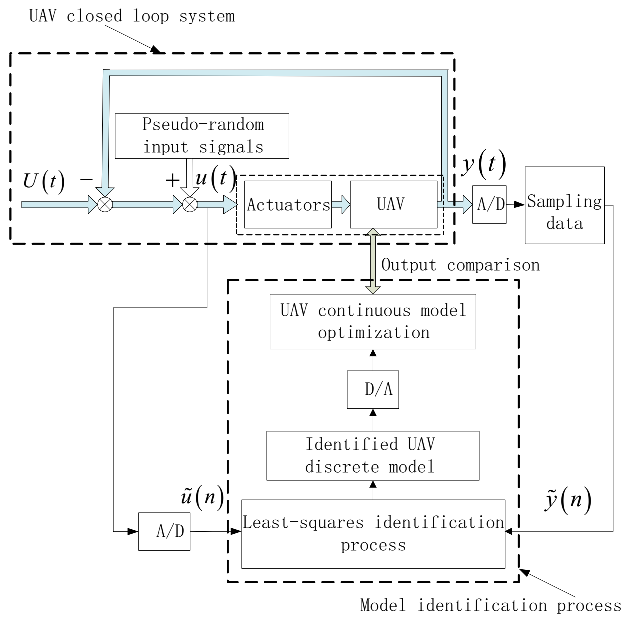

Fig. 1. Swan-UAV system identification process

thing need to be made sure is that the autopilot processing frequency should be high enough to rebuild a continuous-time signal from discrete-time sampling signal. This affects the fidelity of identified models since the sampled signals will be used for later model identification work. In our identification process, the input signal $u(t)$ and output signal $y(t)$ have been sampled and recorded as $\tilde{u}(n)$ and $\tilde{y}(n)$. Besides, for SWAN-UAV, the input signal $u(t)$ is recorded before it is transmitted to actuators, and the output signal $y(t)$ is given by onbaord sensors. So the model developed for SWAN-UAV's certain channel is actually the combined model of SWAN-UAV and corresponding actuator .

The second module in Fig.1 is the model identification process. There are mainly four steps in this module. The first step is to select an identification algorithm for the discrete-time model identification. Several methods can be used in this step, such as nonparametric time domain methods, nonparametric frequency domain methods, parameter estimation methods, etc [15][6]. In our identification process, we select the least-squares method, which belongs to parameter estimation method, to identify the corresponding discrete-time models of a small UAV.

The second step is to derive the small UAV's discrete-time models based on the time domain model identification method.The structure of target models and model orders should be carefully considered and selected. Our main idea for model structure and order selection is that the models derived from similar experiment data should display some similarities, such as they will have almost the same poles and zeros and display same frequency characteristics in a required frequency interval (e.g., from 0.01 to 60 rad/sec). We want to mention readers that a lot of unavoidable disturbance exists in real flight experiments and the models derived for SWAN-UAV are the combined models of actuators and SWAN-UAV itself. In order to get models that can accurately reflect SWAN-UAV system characteristics, the orders selected for discrete-time models should be higher than traditional orders introduced in textbooks.

The third step in second module is to convert identified discrete-time models to continuous-time models, which can be easily accomplished by using inverse Z-transform.

The fourth step here is to derive optimal low order continuous-time models from high order models obtained before. By using the frequency domain identification method, we can get low order models for small UAV in this step. Based on the assumption we made before, frequency similarity will be observed if models are derived from similar experiments. We investigate the frequency characteristics of these high order models and find low order models after frequency data analyzing. The principle of order selection for a low order model is that the model with the selected low order should be capable of display same frequency characteristics with models with high order in a required frequency interval, and the low order is similar to traditional orders in textbooks.

After this step, target SWAN-UAV models are obtained and the following work is the model validation.

B. Test Signal Selection

As mentioned before, test signal selection is important in system identification. For both linear and nonlinear system, the best test signal is white noise signal since its spectrum is unlimited. Other test signals are also used, such as sinusoid and doublet. But they have frequency spectrum limitation. By using white noise as test signal, the dynamic behavior of the object could be excited sufficiently. In practice, a PRS with bounded frequency spectrum is usually used to substitute white noise because of easy generating and reproducing. The feasibility of using PRS as test signal has been demonstrated in [13]. In SWAN-UAV flight experiments, the test signals we selected for SWAN-UAV model identification is also PRS. To our knowledge, it is the first time to realize small UAV system identification by using PRS as test signal.

C. Model Structure

Model structure selection is crucial in a small UAV model identification and different model structures will affect identification results. Several model structures could be used as target identification model structure, such as the finite impulse response (FIR) model, the autoregressive model with external input (ARX), the average model with external input (ARMAX), the autoregressive moving average (ARMA) model, th eBox-jenkins model, etc [16].As we know, the structure of target models should contain smallest number of parameters to accurately represent true system. The criteria for target model structure selection include the loss function and Akaike's Final Prediction Error(FPE). Chunhua compared identification models of different model structures of a small UAV at its speeding up process before take off in [17]. The ARX, ARMAX and Box-jenkins models provided good identification results at here. However, Wu *et al.* discussed the benefits of selection ARX structure for a small UAV in [1]. In our identification process, we use the ARX model structure as SWAN-UAVs target model structure.

Generally, the ARX model of continuous time system can be expressed as

$$A(q)\overline{y}(t) = B(q)\overline{u}(t-n_k) + \overline{\varepsilon}(t) \tag{1}$$

in which, q is the delay operator, $A(q) = I + A_1 q^{-1} + \ldots + A_{n_a} q^{-n_a}$,$B(q) = B_1 + B_2 q^{-1} + \ldots + B_{n_b} q^{-n_b+1}$, $\overline{y}^T(t) = [y(t+1), y(t), \cdots, y(t-n_a+1)]$ is output vector at time t (i.e., velocities, Euler angles), $\overline{u}^T(t-n_k) = [u(t-n_k), u(t-n_k-1), \cdots, u(t-n_k-n_b+1)$ is the previous input vector on which the current output depends (i.e., elevator, aileron, rudder, and throttle), $\overline{\varepsilon}(t)$ denotes the white-noise disturbance vector. n_a here is the order of polynomial composed by $(A_1, \ldots, A_{n_a})$, n_b is the order of polynomial composed by $(B_1, \ldots, B_{n_b})$, and n_k is the pure time delay of the system. As we mentioned in identification process, n_a and n_b of SWAN-UAV will be higher than traditional values in textbooks.

D. Time domain identification

Time domain identification method is adopted at first to derive small UAV's high order models. Though small UAV itself is a continuous time system, the flight experiment data is collected by sampling. So, the identified high order models at first correspond to the high order discrete time models of a small UAV. The corresponding discrete time model of equ.1 can be derived by z-transformation and showed as follows

$$A(z^{-1})\overline{y}(n) = B(z^{-1})\overline{u}(n-n_k) + \overline{\varepsilon}(n) \tag{2}$$

For a single-input and single-output system, predictor of $\overline{y}(n)$ in equ.2 can be reformed as

$$\widehat{y}(k;\widehat{\theta}) = \phi(k)\widehat{\theta} + \varepsilon \tag{3}$$

where the regression matrix $\phi(k) = [y(0)\cdots y(1-n_a), u(1-n_k)\cdots u(2-n_k-n_b); \cdots; y(k-1)\cdots y(k-n_a), u(k-n_k)\cdots u(k-n_k-n_b+1)]$, $\widehat{\theta}^T = [-a_1, \ldots, -a_{n_a}, b_1, \ldots, b_{n_b}]$, $\varepsilon^T = [\varepsilon(1), \ldots, \varepsilon(k)]$.

The loss function can be defined as the sum of square of measurements and predictor, i.e,

$$\min_{\theta} V = \min_{\theta} \sum_{i=1}^{n} \varepsilon^2(i) = \min_{\theta} \sum_{i=1}^{n} |y(i) - \phi(i)\widehat{\theta}|^2 \tag{4}$$

Mathematically speaking, the smaller the cost function is, the lower the prediction error will be, and the more accurate the identified model will be obtained. By acquiring the knowledge of least-squares method, the well-established identified parameter vector can be derived as,

$$\widehat{\theta} = \left[\phi(k)^T \phi(k)\right]^{-1} \phi(k)^T \widehat{y}(k;\widehat{\theta}) \tag{5}$$

The models identified by using equ.5 is the discrete time models of small UAV under research. In order to get continuous time models, we need to use inverse z-transformation to transfer discrete time models to continuous time models.

E. Frequency domain identification

Different from previous model order selection methods, we obtain high order models by the time domain identification method, then decrease model orders by using the frequency identification method. Considering different disturbance of the flight experiments, we set the orders of the target models higher than traditional ones in the time domain identification procedure. And these high order identified models can preserve a small UAV's characteristics in a wider frequency domain. In our perspective, the identified models in similar flight conditions should display similar frequency spectrum characteristics.

Suppose we get a set of high order models $(G_1(s), G_2(s), \cdots, G_n(s))$ for one target model (e.g., SWAN-UAV's longitudinal channel model) under similar flight experiment conditions, the complex frequency response of this set of models can be obtained, and the mean value of the complex frequency response can be expressed as,

$$\overline{F} = \frac{1}{n} \sum_{i=1}^{n} F\left(G_i(s)\right) \tag{6}$$

where $F(G_i(s))$ is the complex frequency response of the model $G_i(s)$.

If the target low order model of SISO continuous system is,

$$\overline{G}(s) = \frac{B(s)}{A(s)} = \frac{b_1 s^n + b_2 s^{n-1} + \cdots + b_{n+1} s^0}{a_1 s^m + a_2 s^{m-1} + \cdots + a_{m+1} s^0} \tag{7}$$

The $(a_1, a_2, \cdots, a_{m+1})$ and $(b_1, b_2, \cdots, b_{n+1})$ of $\overline{G}$ can be estimated by creating linear equations and solving them in

$$\min_{\{a_i\},\{b_i\}} \int_{\omega_i}^{\omega_e} W(\omega) \left|\overline{G}(\omega)A(\omega) - B(\omega)\right|^2 d\omega \tag{8}$$

where ω_i and ω_e are the required starting and ending frequency point, $W(\omega)$ is the weight selected at frequency point ω, $\overline{G}(\omega)$ is the complex frequency response at ω, $A(\omega)$ and $B(\omega)$ are the Fourier transforms of polynomials $(a_1, a_2, \cdots, a_{m+1})$ and $(b_1, b_2, \cdots, b_{n+1})$. Then the low order models of a small UAV which has the same orders with traditional ones can be identified by using frequency domain identification technology.

III. Flight Experiment for SWAN-UAV System Identification

A. Flight Experiment Hardware

1) SWAN-UAV: SWAN-UAV in our experiment is a small fixed-wing commercial aircraft model, which is showed in Fig.2(*a*). The aim of building SWAN-UAV system is to promote SWAN-UAV's comprehensive characteristics in its flight mission. The advantages of using this kind of small aerial vehicle include: 1) it is widely sold and not expensive; 2) there are lots of groups around the world carrying out researches on this kind of small aerial vehicles, so there are more materials can be looked into; 3) it is made by ochroma pyramidale, so its mass is very low and the payload can be increased.

TABLE I
Flight Experiment Hardware Features

SWAN		STA32	
Flight model weight	6.32 Kg	Weight in case	0.15 Kg
Wing span	2110 mm	Case dimensions	$115\times65\times$ 40 mm
Fuselage length	1460 mm	Processing frequency	73 Hz
Fuselage maximum diameter	188 mm	Temperature operation rage	$-25^\circ \sim +70^\circ$

2) Autopilot STA32: The autopilot we used for SWAN-UAV in our flight experiment is STA32. It is a high quality autopilot made by JSC "STC RISSA", Russia. Original STA32 has 3 MEMS accelerometers, 3 MEMS gyroscopes, 3 magnetic sensors, a absolute pressure sensor, a differential pressure sensor and a GPS receiver, and customers are allowed to add additional devices to STA32 to extend the system functionality. Using a special user-friendly constructor software , customers are allowed to write to and read from STA32 control system configuration (CSC), also flight programs and flight program status. Unlike most hardware realized autopilots that neither can control parameters nor CSC be changed, STA32's parameters and CSC can be changed according to ground station commands even in a flight procedure. Besides, STA32 is able to send back 209 kinds of data to ground station through the wireless communication device in real time. 45 kinds of these data are sensors output data. Some features of STA32 are listed in Table I. More details of STA32 can be found on its website.

3) Ground Station: An IBM laptop has been used as the ground station in flight experiments. A special software "Constructor" is installed in this laptop. This laptop is used to build SWAN-UAV CSC, tune parameters, upload and download experiment data, route programming, etc.

(a) (b)

Fig. 2. Flight Experiment Hardware (*a*)SWAN. (*b*)Autopilot STA32.

B. Flight Experiment Procedure

In our flight experiments, there are four closed control loops in SWAN-UAV CSC, including aileron and rudder coordinative control loop, altitude control loop and speed control loop. The control commands from STA32 are four PWM signals for elevators δ_e , ailerons δ_a, rudder δ_r and throttle of engine δ_T.

A set of pseudo-random numbers from a standard Gaussian distribution will be stored in STA32 flash memory before a flight experiment. The PRS $f(t)$ is generated by holding each pseudo-random number for time T

$$f(t) = x_{\lfloor \frac{t}{T} \rfloor}, x \in X \tag{9}$$

in which X is the set of pseudo-random numbers as said before and is bounded in $[-3^\circ \sim +3^\circ]$, T is the holding time. In our flight experiment, T equals 0.2 sec, which is decided based on Shannon sampling law.

The cruise speed in these flight experiments is set to be 22.22m/sec. When SWAN-UAV achieves trimmed flight condition during flight experiments, PRS generated by pseudo-random numbers is injected to SWAN-UAV control input signal by the on-board computer system. The PRS is injected into elevator control signal in longitudinal model identification and into aileron control signal in lateral model identification respectively. For safety consideration, the PRS injection is performed in several small time intervals during flight experiments.

Different experiments have been carried out and a wide range of data for different flight conditions is recorded. We present two particular experiments at here, one of which was for longitudinal model identification fight test and the other was for lateral model identification fight test. There were five times of PRS injection in this longitudinal model identification experiment and eight times of PRS injection in lateral model identification.The flight trajectory altitude information of these two experiments is showed in Fig.3 and Fig.4, which is one of the criteria of trimmed condition.

Thirty two signals are selected and recorded from STA32 in flight experiments, most of which are used to monitor

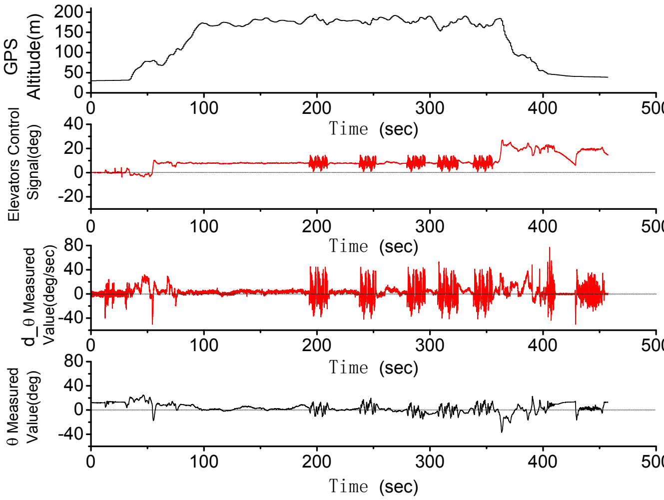

Fig. 3. Recorded signals in longitudinal model identification experiment

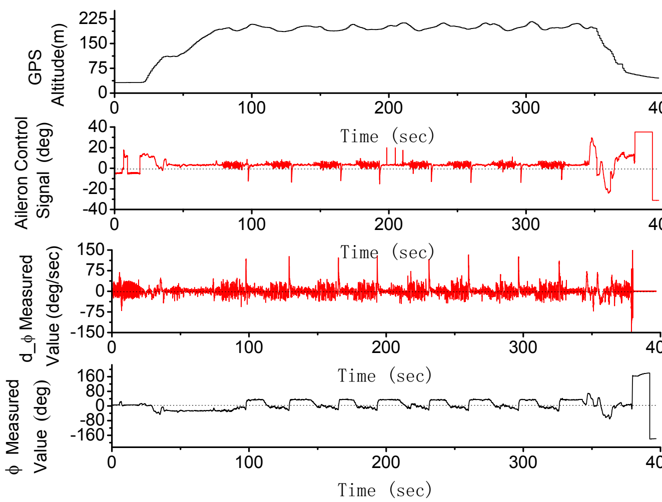

Fig. 4. Recorded signals in lateral model identification experiment

SWAN-UAV flight conditions. The elevators control signal δ_e, pitch rate $\dot{\theta}$ and pitch angle θ in longitudinal model identification are shown in Fig.3. Ailerons control signal δ_a, roll rate $\dot{\phi}$ and roll angle ϕ in lateral model identification are shown in Fig.4. In these two figures, we can see that these state variables doesn't change a lot in trimmed condition.

In Fig.3 and Fig.4, five and eight data segment with heavy oscillation can be observed respectively. These segments of data would be extracted for SWAN-UAV model identification. The elevator input control signals added with pseudo-random signal and pitch rate were used as input and output signals for longitudinal model identification, and the aileron input control signals added with pseudo-random signal and roll rate were used as input and output signals for lateral model identification. Since each set of the data was extracted from single experiment, models identified from these data could be considered to have similar flight conditions and these models should display similarities in frequency domain. For each set of these signals, we kept one segment group for model validation and use all the rest for model identification.

IV. SWAN-UAV System Identification Results

Because the servos we used for actuators are Hitec HS-625MG servos, whose frequency bands are very limited, it is hard to obtain Hitec HS-625MG servos model by on ground experiments. Since servo model identification is not the main aim of our experiment goal and input signal $\tilde{u}(n)$ is sampled before servos, we combined servo models and SWAN-UAV model in our identification models.

According to experience on aerial vehicles, we assumed the hight order models identified by time domain technology shall keep coherence from 0.01 to 60 rad/sec in frequency domain. Traditionally, unsimplified longitudinal and lateral models are fourth order model and actuator model can be first or second order model. We assumed that the target model shall have orders higher than fifth or sixth. To demonstrate our assumption, longitudinal models with $(n_a = 4, n_b = 4)$ were derived and poor coherence of frequency response was observed. Then in longitudinal model identification, we investigated the model with $(n_a = 6, n_b = 6)$ and $(n_a = 8, n_b = 8)$. The best coherence of frequency response was achieved by models with $(n_a = 8, n_b = 8)$ and the frequency spectrum is showed in Fig.5. In order to keep n_a and n_b as small as possible, we did not increase n_a and n_b when identified models could achieve required frequency coherence.

For lateral high order identification, the model with $(n_a = 8, n_b = 8)$, $(n_a = 9, n_b = 9)$, and $(n_a = 10, n_b = 10)$ were investigated, and $(n_a = 10, n_b = 10)$ gave the best results in required frequency interval. The frequency spectrum of $(n_a = 10, n_b = 10)$ is shown in Fig.8.

The $\overline{F}$ from 0.01 to 60 rad/sec of identified longitudinal $(n_a = 8, n_b = 8)$ models is redrawn in Bode diagram, which is shown by red line in Fig.6, and the $\overline{F}$ from 0.01 to 60 rad/sec of identified lateral $(n_a = 10, n_b = 10)$ models is also redrawn in Bode diagram, which is shown by red line in Fig.9.

In model order decreasing step, we assumed actual longitudinal model is second order system and elevator model is first order system and set $(n = 2, m = 3)$. We used $\triangle C_e$ to express input signal to elevators and $\dot{\theta}$ to express output signal of pitch rate, the identified $(n = 2, m = 3)$ model was

$$\frac{\dot{\theta}(s)}{\triangle C_e(s)} = \frac{5.92\left(\left(\frac{s}{48.69}\right)^2 - 2\left(\frac{0.63s}{48.69}\right) + 1\right)}{\left(\frac{s}{24.60} + 1\right)\left(\left(\frac{s}{19.60}\right)^2 + 2\left(\frac{0.58s}{19.60}\right) + 1\right)} \quad (10)$$

For lateral model order decreasing, we assumed actual lateral model is second order system and aileron model is

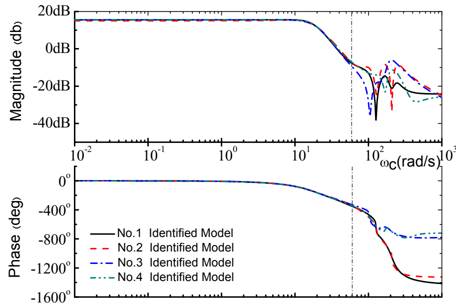

Fig. 5. Frequency characteristics of eighth order identified longitudinal models

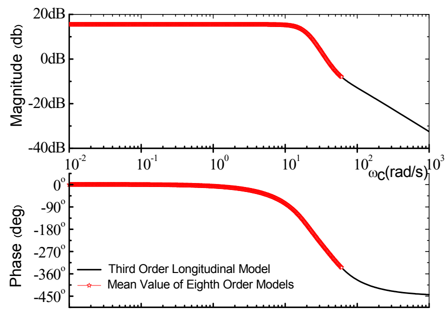

Fig. 6. Third order longitudinal model based on mean value of eighth order models' frequency characteristics

second order system and set $(n = 3, m = 4)$. We used $\triangle C_a$ to express input signal to elevators and $\dot{\phi}$ to express output signal of roll rate, the identified $(n = 3, m = 4)$ model is

$$\frac{\dot{\phi}(s)}{\triangle C_a(s)} = \frac{9.33\left(\frac{s}{33.75}-1\right)}{\left(\left(\frac{s}{19.70}\right)^2+2\left(\frac{0.73s}{19.70}\right)+1\right)} \times \frac{\left(\left(\frac{s}{66.93}\right)^2-2\left(\frac{0.23s}{66.99}\right)+1\right)}{\left(\left(\frac{s}{59.40}\right)^2+2\left(\frac{0.79s}{59.40}\right)+1\right)} \tag{11}$$

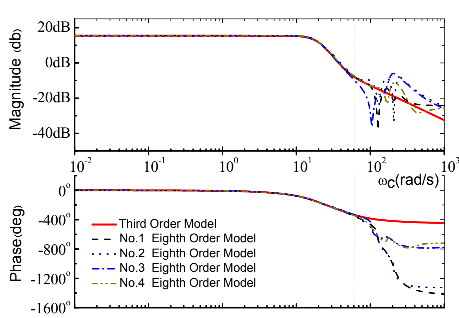

Fig. 7. Frequency domain verification of third order identified longitudinal model

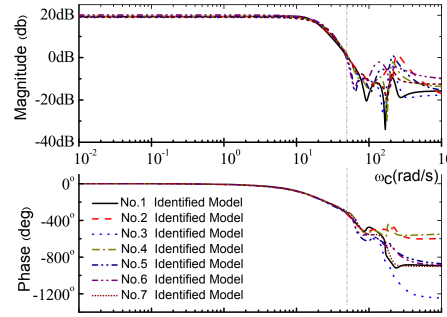

Fig. 8. Frequency characteristics of tenth order identified longitudinal models

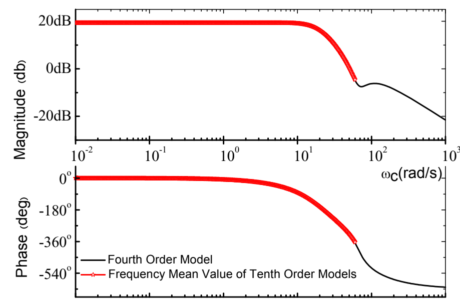

Fig. 9. Fourth order lateral model based on mean value of tenth order models' frequency characteristics

V. SWAN-UAV Identified Model Validation

Model validation is the last important step in SWAN-UAV model identification procedure. First, we validated identified models in equ.10 and equ.11 in frequency domain. The frequency spectrum of identified longitudinal $(n = 2, m = 3)$ model is compared with $(n_a = 8, n_b = 8)$ models in Fig.7, and the frequency spectrum of identified lateral $(n = 3, m = 4)$ model is compared with $(n_a = 10, n_b = 10)$ models in Fig.10. From 0.01 to 60 rad/sec in frequency domain, great coherence of the low order model and high order models frequency characteristics can be observed in both figures.

Then, we validated identified models in equ.10 and equ.11

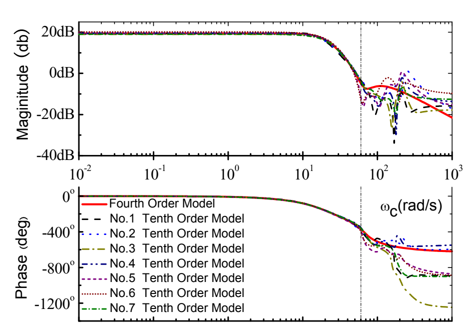

Fig. 10. Frequency domain verification of fourth order identified lateral model

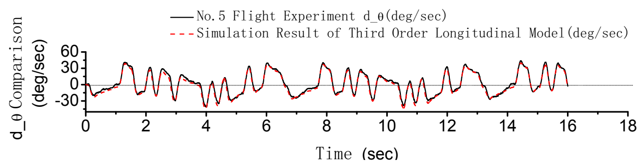

Fig. 11. Time domain model validation for identified third order longitudinal model

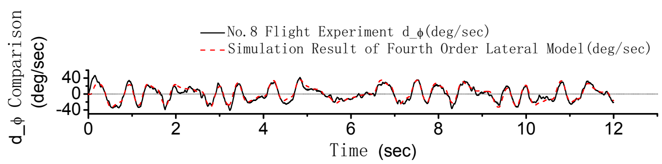

Fig. 12. Time domain model validation for identified Fourth order lateral model

in time domain. One group of signal segments extracted from longitudinal model identification flight experiment was used in time domain model validation. The flight control input signal δ_e was input to equ.10 in simulation program, and the simulation output of this model was recorded and compared with flight experiment pitch rate response in Fig.11. Also, another group of signal segments extracted from lateral model identification flight experiment was used for lateral model validation. The flight control input signal δ_a was input to equ.11 and the simulation output was recorded and compared with flight experiment roll rate response in Fig.12. From these two figures, we find that the identified low order models can successfully generate same outputs as real SWAN-UAV.

VI. CONCLUSION

The system identification method for a small unmanned aerial vehicle model identification was stated in this paper. The test signal selected for the proposed method is pseudo-random signal. After compared several model structures, ARX structure was selected as target model structure. Time domain model identification technology is adopted to obtain high order models that have coherent characteristics in required frequency interval. Then, frequency domain model identification technology is used to generate low order models from high order models obtained in time domain identification technology. This proposed system identification method has been applied to SWAN-UAV longitudinal and lateral model identification task. Model validations in both frequency domain and time domain proved the fidelity of identified models and feasibility of the proposed method.

The main contribution of this paper is the combination of time domain and frequency domain model identification technologies, leading the method proposed here has the advantages of both of these two technologies. Besides, pseudo-random signal is used in small unmanned aerial vehicle model identification for the first time.

All the system identification calculations in this paper were finished off-line identification. In the future work, we want to extend SWAN-UAV model identification from off-line identification to on-line identification. Beside, optimal autopilots will be derived based on identified models obtained here. So, better controllability and stability of SWAN-UAV can be achieved in its flight missions.

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